Location Selection Strategy of Distribution Centers Based on Artificial Fish Swarm Algorithm Improved by Bacterial Colony Chemotaxis

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Abstract

The distribution center (DC) is crucial in the connection between the suppliers and customers, thus the strategy for the selection and optimization of distribution center location plays an important role in logistics systems. In order to minimize the total cost, a distribution center location model with the lowest total cost is established. Accordingly, a distribution center location strategy based on artificial fish swarm algorithm improved by bacterial colony chemotaxis (BCC-AFSA) is proposed aiming to obtain a more feasible distribution center location strategy promptly. The algorithm of BCC-AFSA applies bacterial colony chemotaxis (BCC) to artificial fish swarm algorithm (AFSA) when the results do not change or change infinitesimally after multiple iterations. As result, the global optimization ability of the algorithm is improved. Through algorithm tests and example simulation, it is shown that the improved BCC-AFSA is more effective in the location selection strategy of distribution centers.

Keywords: Distribution center, Bacterial colony chemotaxis, Artificial fish swarm algorithm, Location, Strategy

1 Introduction

Logistics industry has developed rapidly with the development of the Internet, in which the selection and optimization for the location of distribution centers is regarded as an important part [1]. The location of distribution center refers to the optimization process of selecting a certain number of distribution center locations within the range of a quantity of supply centers and demand points. The distribution center is an important bridge that connects the suppliers and customers. As a key segment of logistics system, it determines the distribution distance, cost and distribution mode of logistics, which further affects the efficiency of the logistics industry [2-4]. Therefore, the research on distribution centers location problem is of great significance. However, the location selection problem of logistics distribution centers involves innumerable variables and constraints [5]. Hence, some traditional methods are difficult to solve the problem. Some swarm intelligence algorithms have been researched in recent years.

In this paper, artificial fish swarm algorithm improved by bacterial colony chemotaxis (BCC-AFSA) is used in a location selection strategy of distribution centers. Aiming to change the shortcomings such as falling into local optimum easily, low search accuracy and no high convergence speed in artificial fish swarm algorithm (AFSA), we introduce bacterial colony chemotaxis (BCC) algorithm to enhance the local search ability and population diversity of the algorithm, which prevents the algorithm from falling into local optimization due to the loss of population diversity, and thus improves the global search ability and convergence speed of the algorithm. In the establishment of the distribution center location model with the lowest total cost, BCC-AFSA is adopted to solve the problem, which solves the problem of high total cost and improves the logistics operation efficiency of enterprises. In the location model for selecting the distribution centers with the lowest total cost, BCC-AFSA is adopted to solve the problems of high total cost, leading to the improvement of the logistics system efficiency.

2 Literature Review

Shang et al. [6] proposed an improved whale optimization algorithm to solve the location selection problem of logistics distribution centers, aiming to overcome the drawback of easily trapping in local optimization in traditional heuristic algorithms, which leads to the reduction of efficiency of logistics system. Xiaoping Xu et al. [7] introduced a quasi-opposition learning spider monkey optimization algorithm based on Laplace distribution (LOBSMO) in order to quickly obtain a reasonable logistics distribution center

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location scheme. Yu et al. [8] proposed an improved particle swarm optimization algorithm to solve the location problem of distribution centers. Jilu Li et al. [9] applied the adaptive immune algorithm to the distribution center model, which adds the distance limit to the penalty mechanism aiming at the minimum cost. Moreover, the adaptive crossover probability and mutation probability are developed according to the affinity between the antibody and the antigen, and the simulation results verify that the algorithm is effective in the location selection of distribution centers. Min Liu [10] presented a modified flower pollination algorithm for solving the location selection problem of logistics distribution centers, which aims at solving the general existing problems such as low accuracy, slow speed and small scale in current algorithms for choosing logistics distribution center location. Qun Yuan et al. [11] built an improved hybrid genetic algorithm by the combination of the genetic algorithm and the tabu-search algorithm in order to solve the location selection problem, using the greedy algorithm to improve the crossover operator. Kun Wang et al. [12] proposed a logistics distribution center location strategy based on ant colony algorithm.

The research of distribution center location in China started late, with the development of intelligent algorithm, some scholars begin to apply intelligent algorithm to the location of distribution center in recent years. For the model of distribution center location problem, the distribution center location model mentioned in the above literature is generally the distribution center location model of the first level transportation network, that is,on the premise that n demand points are known, m distribution centers should be set among them, so as to minimize the transportation cost between the selected distribution center and the demand points within the distribution scope. The above model only considers the transportation network from the distribution center to the customer level, and does not consider the transportation network from the factory to the distribution center. The cost only considers the transportation expenses, and other expenses such as fixed expenses and circulation expenses are not included in the total cost. In recent years, swarm intelligence algorithm such as whale optimization algorithm, particle swarm optimization and genetic algorithm have applied to the model of distribution center location. However, the swarm intelligence algorithm for model solving still needs to be explored, more intelligent algorithms to solve the location of distribution center, especially the improved ones, need to be explored to achieve the purpose of seeking lower cost. In this paper, a distribution center location model considering from factory to distribution center and then to customer is established. The primary transportation cost, secondary transportation cost, fixed cost of distribution centers and distribution center circulation transfer cost are included in the total cost, so that the model is closer to the reality. In this paper, a new improved fish swarm algorithm is proposed to solve the location model of distribution center. The new improved fish swarm algorithm is more effective in finding lower cost.

3 Artificial Fish Swarm Algorithm (AFSA)

x_i is the current position of artificial fish AF_i, $f(x_i)$ is the food concentration at position x_i, *Visual* and δ are visual range and crowding factor of artificial fish, respectively. *Step* is the moving step length of artificial fish

(1) Prey behavior

After finding food, artificial fish swim to places with more food. The current position of the artificial fish is x_i, and then the artificial fish randomly selects a new position x_j within its visual range, If $f(x_j)$ is better than $f(x_i)$, then the artificial fish will swim one step to x_j. At this time, update x_i's position, that is:

$$x_i \leftarrow x_i + rand(\ ) \bullet Step \bullet \frac{x_j - x_i}{\|x_j - x_i\|} \quad \textbf{(1)}$$

Otherwise, the artificial fish will try another position at random to determine whether to swim to a new position with higher food concentration. After many attempts, if the artificial fish does not swim to a new position, it will swim to a random position, that is:

$$x_i \leftarrow x_i + rand(\ ) \bullet Step \quad \textbf{(2)}$$

(2) Swarm behavior

In order to share food and avoid danger, fish naturally swarm during swimming. Artificial fish AF_i looks for other artificial fish AF_c in its visual range, position is x_c. If $f(x_c)$ is better than $f(x_i)$, and the crowding degree of x_c is less than δ, the artificial fish will swim to x_c. At this time, update x_i's position, that is:

$$x_i \leftarrow x_i + rand(\ ) \bullet Step \bullet \frac{x_c - x_i}{\|x_c - x_i\|} \quad \textbf{(3)}$$

Otherwise, foraging behavior should be carried out.

(3) Follow behavior

When artificial fish find food, nearby fish will also swim and get food. Artificial fish find other artificial fish in its field of vision. The food concentration of the adjacent fish was calculated to get the maximum food concentration, and the position is $x_{\max}$. If $f(x_{\max})$ is better than $f(x_i)$, and the crowding degree of $x_{\max}$ is less than δ, the artificial fish will swim one step to $x_{\max}$. At this time, update x_i's position, that is:

$$x_i \leftarrow x_i + rand(\ ) \bullet Step \bullet \frac{x_{\max} - x_i}{\|x_{\max} - x_i\|} \tag{4}$$

Otherwise, foraging behavior should be carried out.

4 The Establishment of the Model with Distribution Center Location Strategy

The location strategy of distribution center is complex optimal combination problem, which solves that: when the location of the factory is given, a certain number of distribution centers should be selected from the alternative distribution centers, minimizing the total cost from the factory to the selected distribution centers and then towards the customers. i stands for the factory, and its set is I. j stands for the distribution center, and its set is J. k stands for customer, and its set is K. The parameters required for model establishment are shown in Table 1.

Table 1. Model parameters

Parameters	Meaning
Z_1	primary transportation cost
m	number of distribution centers
w_{ij}	transportation volume from *i* to *j*
a_{ij}	transportation cost per unit distance between *i* and *j*
(x_j, y_j)	coordinate of *j*
n	number of customers
x_{jk}	transportation volume from *j* to *k*
b_{jk}	transportation cost per unit distance between *j* and *k*
Z_3	fixed cost of distribution centers
Z_4	circulation cost of distribution centers
Z	total cost
P	maximum number of constructed distribution centers
M_j	maximum capacity of *j*
l	number of factories
h_{ij}	unit transportation cost from *i* to *j*
d_{ij}	distance between *i*and *j*
(x_i, y_i)	coordinate of *i*
Z_2	secondary transportation cost
c_{jk}	unit transportation cost from *j* to *k*
d_{jk}	distance between *j* and the *k*
(x_k, y_k)	coordinate of *k*
F_j	fixed charge of *j*
μ_j	commodity circulation charge of *j*
D_k	demand quantity of *k*
C_i	maximum production capacity of *i*

(1) The primary transportation cost, which refers to the transportation cost from the factory to the distribution centers.

$$Z_1 = \sum_{i=1}^{l}\sum_{j=1}^{m} h_{ij} w_{ij} \tag{5}$$

$$h_{ij} = d_{ij} * a_{ij} \tag{6}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{7}$$

(2) The secondary transportation cost, which is the transportation cost from distribution center to the customers.

$$Z_2 = \sum_{j=1}^{m}\sum_{k=1}^{n} c_{jk} x_{jk} \tag{8}$$

$$c_{jk} = d_{jk} * b_{jk} \tag{9}$$

$$d_{jk} = \sqrt{(x_j - x_k)^2 + (y_j - y_k)^2} \tag{10}$$

(3) The fixed cost of distribution centers, which includes the construction cost, fixed assets depreciation cost and management cost of distribution centers.

$$Z_3 = \sum_{j=1}^{m} z_j F_j \tag{11}$$

$$z_j = \begin{cases} 1 & \text{select distribution center j} \\ 0 & \text{others} \end{cases} \tag{12}$$

(4) The circulation cost of distribution centers.

$$Z_4 = \sum_{i=1}^{l}\sum_{j=1}^{m} \mu_j w_{ij} \tag{13}$$

It is necessary to establish some assumptions for the model, as follows:

(1) Optimal distribution center is selected from a certain set of alternative distribution centers;

(2) Only one kind of goods distribution is considered, and the goods to be distributed are completed in one time;

(3) The distance and the transportation cost per unit distance between factory and distribution center as well as those between distribution center and customer are provided. Meanwhile, the demand quantity of each customer is known.

(5) Transportation cost increases with the increase of transportation volume, unit transportation cost increases with the increase of transportation distance;

(6) The fixed construction cost of distribution centers are given, Alternative distribution centers are known.

Above all, location selection strategy model of distribution centers aiming at the lowest total cost is investigated:

$$\min Z = Z_1 + Z_2 + Z_3 + Z_4 \tag{14}$$

S.T.

$$\sum_{j\in J} x_{jk} \ge D_k \quad k \in K \tag{15}$$

$$\sum_{j\in J} z_j \le P \tag{16}$$

$$\sum_{j\in J} y_{jk} = 1 \quad k \in K \tag{17}$$

$$\sum_{k\in K} x_{jk} = \sum_{i=I} w_{ij} \quad j \in J \tag{18}$$

$$\sum_{j\in J} w_{ij} \le C_i \quad i \in I \tag{19}$$

$$\sum_{i\in I} w_{ij} \le M_j \quad j \in J \tag{20}$$

$$w_{ij} \ge 0,\ x_{ij} \ge 0 \quad i \in I,\ j \in J,\ k \in K \tag{21}$$

Where, y_{jk} represents whether k is delivered by j. k is delivered by j if y_{jk} is 1, otherwise y_{jk} is 0.

Eq. (15) indicates that the distribution volume of the distribution center can meet the needs of customers. Eq. (16) is the maximum number of distribution centers. Eq. (17) yields that each costumer is provided distribution service by only one distribution center. Eq. (17) ensures that each customer is delivered by only one distribution center. Eq. (18) denotes that the commodity quantity getting in and out of each distribution center is the same. Eq. (19) means that the commodity quantity sent by the factory to the distribution center does not exceed its maximum production capacity. Eq. (20) shows that the commodity quantity sent from the factory to the distribution center is no more than the maximum capacity of the distribution center.

5 AFSA Improved by Bacterial Colony Chemotaxis (BCC-AFSA)

AFSA algorithm has a strong ability to find the optimal value at the beginning of the algorithm, however, the artificial fish tends to gather or swim randomly near the local optimum solution in the later stage of operation. Thus, it easily falls into the local optimal result, obtains the global optimal result difficultly and leads to slow convergence rate [13]. In order to overcome this drawback, the algorithm of bacterial colony chemotaxis is introduced into the later stage of AFSA, when the bulletin board does not change or change infinitesimally after the maximum iteration number reaches. In the algorithm of bacterial colony chemotaxis, the step size of each bacterium is determined according to the probability distribution, thus resulting in the performance of breaking the limit of local optimum. In the meantime, the migration of bacterial colonies contributes to the escape from local optimum, which helps the bacteria move towards the optimal direction by interacting information with each other and thus enhances the global optimization ability of the algorithm.

Bacteria are simple single-celled organisms, and previous studies show that bacteria have some special properties in the chemoattractant environment. Bacterium apperceives the information around it and then determines the next location. This property of bacteria is called chemotaxis, which is the directed motion of bacteria toward environmental conditions it deems attractive. BCC is an artificial intelligence optimization from the chemotaxis property of bacterial [14-15].

The procedures of BCC-AFSA are described as follows:

(1) Initialize the parameters of AFSA, including total fish number, the size of step, the search vision scope, iterations, the maximum number of iterations, and the number of iterations when the bulletin board is unchanged, etc.

(2) Initialize the fish swarm and the billboard. Artificial fishes in a certain scale are generated randomly, and the fish swarm is initialized. Then, the optimal value of the calculated artificial fish is selected and recorded on the bulletin board for initialization.

(3) Execute AFSA. Each artificial fish performs a series of operations, including swarm behavior, follow behavior, prey behavior and random behavior, updating its position simultaneously.

(4) Decide whether BCC algorithm is introduced. If the number of iterations when the bulletin board remains unchanged reaches the maximum number, then continue step (5), else skip to step (6).

(5) Apply BCC algorithm, and set the iteration number when the bulletin board remains unchanged to zero. The procedures of BCC algorithm are as the following:

Initialize the algorithm parameters. If the expected calculation accuracy is ε, then T0, b and τ_c are determined by Eq. (22)~(24).

$$T_0 = \varepsilon^{0.30} \times 10^{-1.73} \tag{22}$$

$$b = T_0\left(T_0^{-1.54} \times 10^{0.60}\right) \tag{23}$$

$$\tau_c = \left(\frac{b}{T_0}\right)^{0.31} \times 10^{-1.16} \tag{24}$$

Assume the movement velocity of the bacterium is v, which is set as an invariant constant. In order to calculate the new motion direction of the bacterium, the motion direction of n dimensions can be described by an angle vector of n-1 dimensions $\phi = (\phi_1, \phi_2, .. \phi_{n-1})$. In two dimensions of $(i, i+1)$, suppose $i(i = 1, 2, 3, .., n)$ as the dimension number, the new movement angle of the bacterium is determined by angle ϕ. The probability distribution toward left or right submits to two equal Gaussian probability distributions.

$$P\left(x_i = \phi_{i,} \upsilon_i = \pm\mu_i\right) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(\phi_i - \mu_i)^2}{2\sigma_i^2}} \tag{25}$$

Where, $\phi_i \in [0°, 180°]$, else,

$$P\left(x_i = \varphi_i\right) = \frac{1}{2}\left[P\left(x_i = \varphi_i, \ \upsilon_i = \mu_i\right) + P\left(x_i = \varphi_i, \ \upsilon_i = -\mu_i\right)\right]$$

Where, the expectation value μ_i and standard deviation σ_i of x_i are given by Eq. (26) and Eq. (27).

$$\mu_i = E\left[x_i\right] = \begin{cases} 62°, \dfrac{f_{pr}}{l_{pr}} \geq 0 \\ 62°\left(1 - \cos\theta\right), \dfrac{f_{pr}}{l_{pr}} < 0 \end{cases} \tag{26}$$

$$\sigma_i = \sqrt{\text{var}\left(x_i\right)} = \begin{cases} 26°, \dfrac{f_{pr}}{l_{pr}} \geq 0 \\ 26°\left(1 - \cos\theta\right), \dfrac{f_{pr}}{l_{pr}} < 0 \end{cases} \tag{27}$$

Where, f_{pr} is the difference of the fitness values between the current position and the previous position; l_{pr} is the mode of the vector connecting the current position and the previous position.

$\cos\theta = e^{-\tau_c \tau_{pr}}$, where τ_{pr} is the duration of the previous movement track of the bacterium. The angle vector of the new movement is determined by the summation of the new angle $\phi = (\phi_1, \phi_2, .. \phi_{n-1})$ and the previous angle.

Calculate the duration time τ of the movement toward the new direction, which preys the exponential probability distribution:

$$P\left(x_i = \tau_i\right) = \frac{1}{T} e^{-\tau_i / T} \tag{28}$$

Where, the parameter T is determined by Eq. (29).

$$T = \begin{cases} T_0, \dfrac{f_{pr}}{l_{pr}} \geq 0 \\ T_0\left(1 + b\left|\dfrac{f_{pr}}{l_{pr}}\right|\right), \dfrac{f_{pr}}{l_{pr}} < 0 \end{cases} \tag{29}$$

Explore the new position. The coordinate $(X_1, X_2, .. X_n)$ in n dimensions is defined to describe the position of the bacterium, where the absolute step size r and $\phi = (\phi_1, \phi_2, .. \phi_{n-1})$ of $n-1$ angles are utilized for the definition of n-dimensional step size $\left(x_1, x_2, ..., x_n\right)$.

$$r = v\tau \tag{30}$$

$$x_1 = r\prod_{k=1}^{n-1}\cos\left(\phi_k\right) \tag{31}$$

$$x_i = r\sin\left(\phi_{i-1}\right)\prod_{k=1}^{n-1}\cos\left(\phi_k\right), i = 2, ..., n-1 \tag{32}$$

$$x_n = r\sin\left(\varphi_{n-1}\right) \tag{33}$$

The bacterium gains a new position by the summation of the new step size $\left(x_1, x_2, ..., x_{n-1}\right)$ and the previous position coordinate. So the new position $x_{inew,k+1}$ at $k+1$ step can be obtained by the above procedures when the bacterium moves k steps.

Calculate the position of the optimal center coordinate. When a bacterium adjusts its movement state, it senses its surroundings before moving to a new position, and then moves toward the center of these bacteria that have better positions. The center of the bacteria with better positions perceived by bacterium i is determined by Eq. (34).

$$\begin{aligned} Center(x_i, k) = Aver(x_{j,k} \mid f(x_{j,k}) < f(x_{i,k}) \cap \\ dis(x_{j,k}, x_{i,k}) < SenseLimite) \end{aligned} \tag{34}$$

$$Aver(x_1, x_2, ... x_n) = \left(\sum_{i=1}^{n} x_i\right) \Big/ n \tag{35}$$

Where, $dis(x_{j,k}, x_{i,k})$ is the distance between bacterium i and bacterium j. The determined central coordinate position is $x_{i,k+1}^{'}$. Compare the values of $x_{i,k+1}^{'}$ and $x_{inew,k+1}$, if $f(x_{i,k+1}^{'}) < f(x_{inew,k+1})$, then the bacterium moves to $x_{inew,k+1}$ at $k+1$ step, otherwise moves to $x_{i,k+1}^{'}$. The step size towards $x_{i,k+1}^{'}$ is $rand() \bullet dis(x_{i,k}, Center(x_{i,k}))$, where $rand()$ obeys uniform distribution of (0, 2).

Judge whether the termination conditions of BCC algorithm are satisfied, the stop condition of BCC algorithm is whether the BCC algorithm reaches the maximum number of cycles. If yes, move to step (6), otherwise return to step (a).

(6) Judge whether the terminal conditional is over, if yes, end the optimization, otherwise move to step (3).

The pseudo code program of BCC-AFSA algorithm is described as follows:

Initialize the parameters of AFSA, include maximum number of iterations NC_{max}, maximum limit of iterations without change of bulletin board $N_{n\max}$.

Initialize the fish swarm and the billboard.

Execute AFSA.

if $N_n = N_{n\max}$

Introducing BCC algorithm

else

if $NC = NC_{max}$

end

else

go to step3

end

The flow chart of BCC-AFSA algorithm is shown in Figure 1.

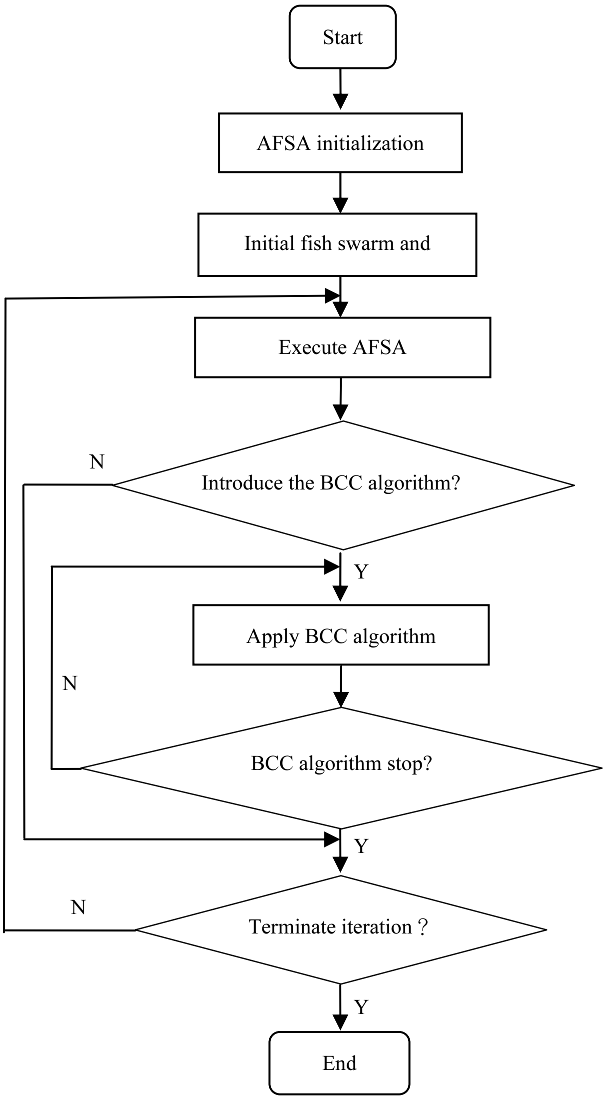

Figure 1. The flow chart

6 Example Simulations

6.1 BCC-AFSA Test

In order to test the performance of the new improved algorithm, two typical functions, 30-dimentional Rotated hyper-ellipsoid function and 20-dimentional Step function are utilized for testing.

F1: Rotated hyper-ellipsoid function

Rotated hyper-ellipsoid function is shown in reference [16], which global optimum is 0.It is a continuous unimodal convex function, which is an extension of hyper-ellipsoid function, also known as the sum of squares function, as shown in Figure 2.

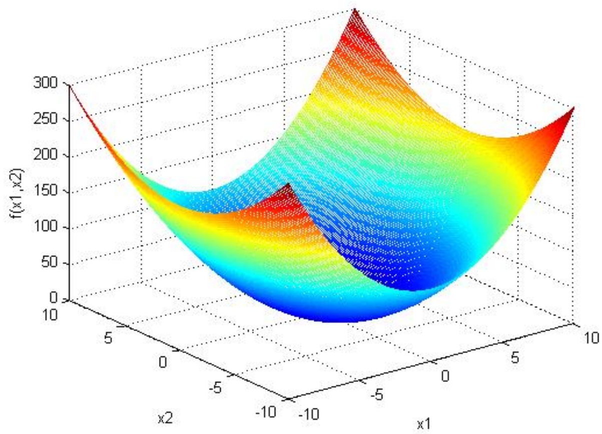

Figure 2. Rotated hyper-ellipsoid function

The tests parameters of Rotated hyper-ellipsoid are function are set as follows: total number of artificial fish is 50, the attempts is 5, the search vision scope is 3, the congestion factor is 0.618, the size of step is 1, maximum threshold value of no-change iteration number is 3. The dimension of bacteria $D = 2$, the initialized position of bacteria is a random number of $[0, 2\pi]$, and the movement velocity of bacteria is 1.

F2: Step function

Step function is shown in reference [16], which global optimum is 0.Step function is a multi-peaked function, which has multiple local optimum points for its multiple platforms. In the whole process of optimization, it is easy to fall into local optimum. Thus, only the algorithm with remarkable global search ability can obtain the global optimum successfully. The function is shown in Figure 3 [16].

The test parameters of Step function is the same as those of Rotated hyper-ellipsoid function.

The superiority of BCC-AFSA is measured by four quantitative indicators such as search accuracy, reliability, operation speed and stability [17]. Search accuracy refers to the comparison of the best value, the worst value and the average value of the optimization algorithm when iterations are fixed. Reliability represents the success ratio of the algorithm. The success rate is the ratio of the operation times reaching the threshold level to the total operation times as an effective threshold is set. Operation speed refers to the average number of iterations and the operation time of the algorithm. Reliability is the standard deviation of the algorithm.

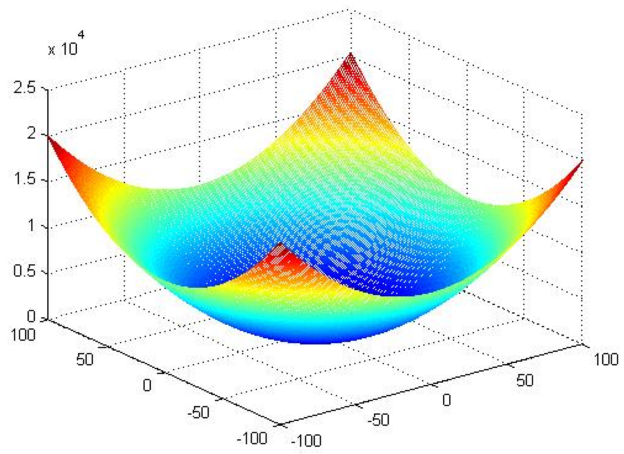

Figure 3. Step function

Table 2 illustrates the search accuracy comparison of F1 function using AFSA, BCC-AFSA and AASFA2, where iterations is 200 and the experiment operates independently for 30 times. Table 3 shows the reliability, operation speed and stability of F1 function employing AFSA and BCC-AFSA, where the threshold level is set to 2.5. Figure 4 and Figure 5 demonstrate the movement of optimal coordinates of F1 function applying AFSA and BCC-AFSA, respectively. The circle in the picture represents the position of each artificial fish. Figure 6 yields the comparison on the two optimization curves of F1 function.

Table 2. The search accuracy comparison (F1)

	Best	Worst	Ave.
AFSA	2.3520	16.4120	5.4666
BCC-AFSA	0E-50	0E-50	0E-50
AASFA2 [18]	1.6301 E-25	3.3276 E-22	6.4746 E-23

Table 3. The reliability, operation speed and stability (F1)

	Success rate	Mean algebra	Calculation time(s)	Standard deviation
AFSA	20%	98.100	16.088	4.307
BCC-AFSA	100%	30.300	5.596	0.000

Table 4 indicates the search accuracy comparison of F2 function using AFSA, BCC-AFSA and AASFA2, where the fixed number of iterations is set to 200 and the experiment operates independently for 30 times. Table 5 shows the reliability, operation speed and stability of F2 function applying AFSA and BCC-AFSA, where the threshold level is set to 100. Figure 7 and Figure 8 show the movement of optimal coordinates of F2 function using AFSA and BCC-AFSA, respectively. The circle in the picture represents the position of each artificial fish. Figure 9 demonstrates the comparison on the two optimization curves of F2 function.

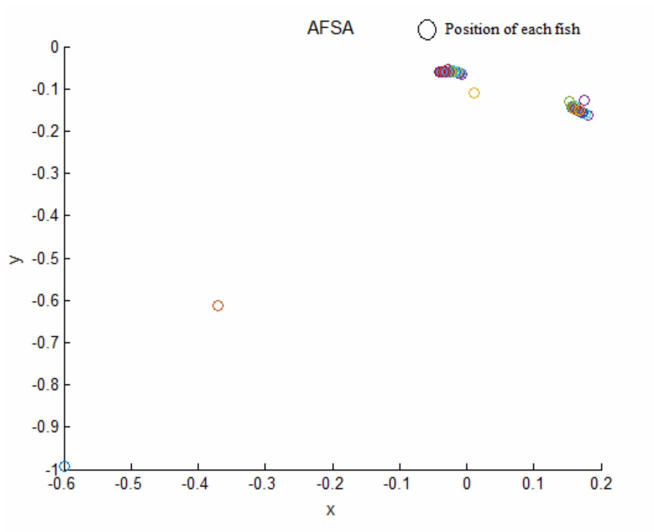

Figure 4. Optimal coordinates of AFSA (F1)

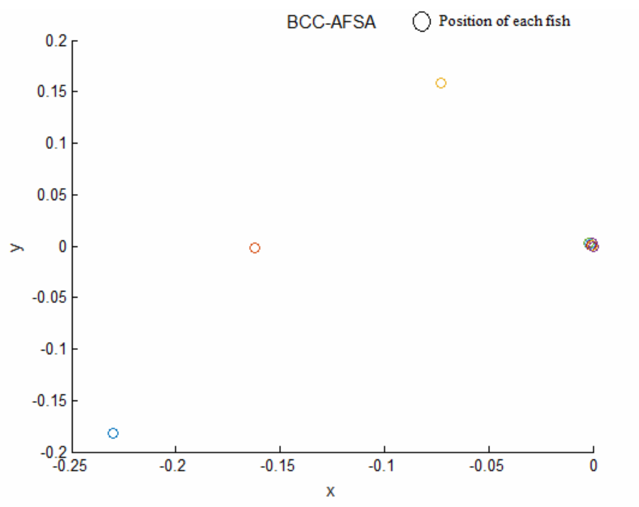

Figure 5. Optimal coordinates of BCC-AFSA (F1)

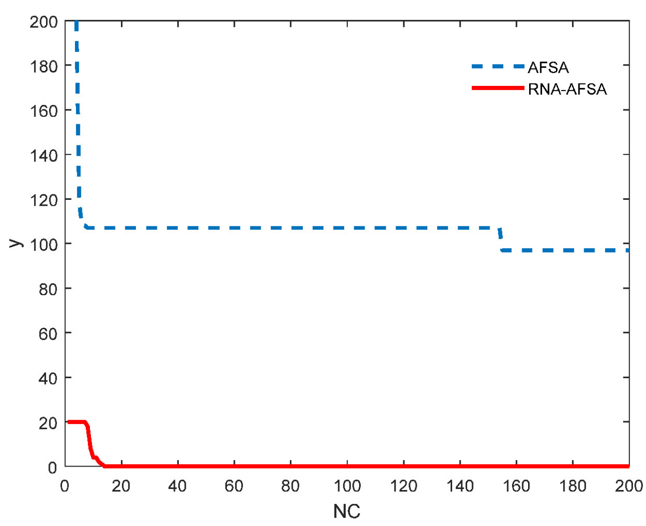

Figure 6. Comparison on the two optimization curves (F1)

Table 4. The search accuracy comparison (F2)

	Best	Worst	Ave.
AFSA	97.000	160.000	128.100
BCC-AFSA	0E-50	0E-50	0E-50
DSMFSA [19]	0E-5	0E-5	0E-5

Table 5. The reliability, operation speed and stability (F2)

	Success rate	Mean algebra	Calculation time(s)	Standard deviation
AFSA	10%	71.100	20.601	18.735
BCC-AFSA	100%	32.000	6.558	0.000

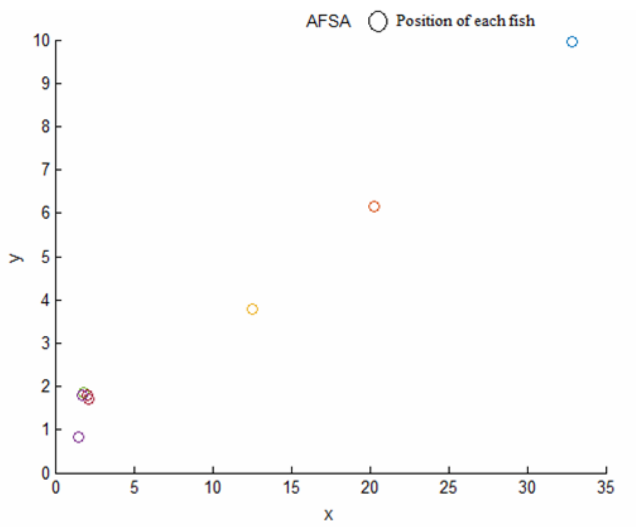

Figure 7. Optimal coordinates of AFSA (F2)

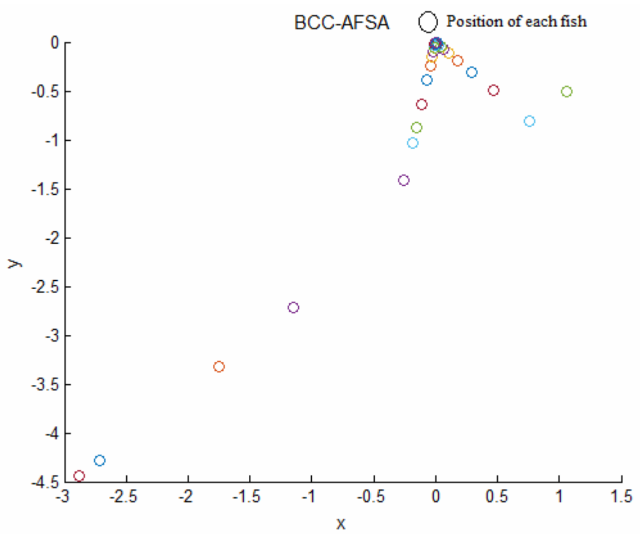

Figure 8. Optimal coordinates of BCC-AFSA (F2)

It can be derived from the experimental results that:

(1) Search accuracy: Compared with other algorithms, BCC-AFSA is feasible to obtain the global optimum regardless of the limitation of local optimum and achieve satisfied optimization results. Moreover, the search accuracy of the average solution is higher than other algorithms as well. It can be indicated from the

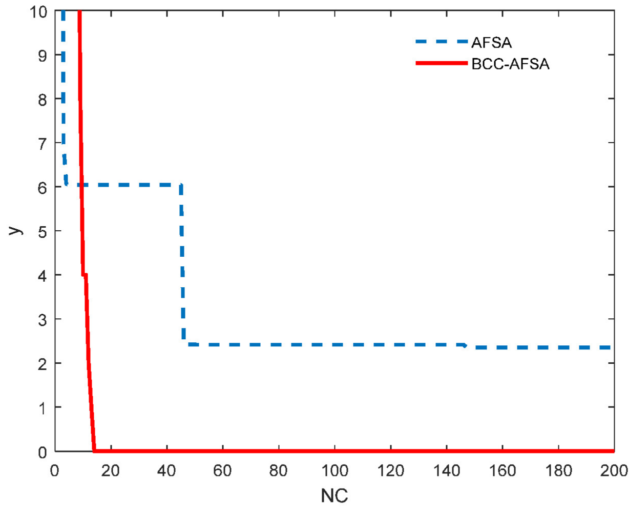

Figure 9. Comparison on the two optimization curves (F2)

movement of optimal coordinates of BCC-AFSA that more artificial fishes cluster around the global optimum. Because of the moving step size and migration activity of bacterial colony chemotaxis algorithm, the algorithm can effectively jump out of local optimum. Because of the communication between bacteria, the global optimization ability is increased. Due to the role of the two parts, the search accuracy of the improved algorithm in Table 2 and Table 4 is greatly improved.

(2) Reliability and operation speed: The success rate of BCC-AFSA is 100%, which is higher than AFSA. As for the operation speed, the average convergence generation and calculation time of BCC-AFSA are both smaller than AFSA. Hence, BCC-AFSA has the merit of better reliability and operation speed.

(3) Stability: The standard deviation of BCC-AFSA is less than that of AFSA, so that the stability of BCC-AFSA is better.

6.2 Simulation Experiments of the Location Selection for Distribution Centers

Given that the coordinate of a manufacturer factory is (266, 153), and no more than 3 of the 10 alternative distribution centers should be selected for the delivery to 20 customers. Table 6 shows the coordinates of the customers and Table 7 indicates the coordinates of the alternative distribution centers. Suppose the delivery cost per unit distance is 5 between factory, distribution centers and customers. Table 8 shows the capacity, fixed assets and circulation transfer costs of the alternative distribution centers. Table 9 refers to the demand quantity of the customers. The parameters are set as follows: iterations is 100, the times of attempts is 5, total number of artificial fish is 10, vision scope is 4, the step size is 1, the congestion factor is 0.618, the dimension of bacteria $D = 2$, the initialized position of bacteria is a random number of, movement velocity of bacteria is 1.

Table 6. customer location

NO.	Location	NO.	Location
1	(255,131)	11	(183,140)
2	(248,164)	12	(217,142)
3	(240,143)	13	(220,140)
4	(215,130)	14	(241,149)
5	(207,142)	15	(254,155)
6	(194,165)	16	(223,129)
7	(190,130)	17	(251,134)
8	(186,156)	18	(237,138)
9	(262,133)	19	(212,160)
10	(210,154)	20	(203,135)

Table 7. Alternative distribution center location

NO.	Location	NO.	Location
1	(194,139)	6	(239,154)
2	(202,155)	7	(237,161)
3	(217,162)	8	(213,190)
4	(229,136)	9	(223,169)
5	(254,148)	10	(263,139)

Table 8. The capacity, fixed investment and circulation transfer fee

NO.	1	2	3	4	5
Fixed investment	310	280	400	280	380
Capacity	50	45	60	48	75
Circulation transfer fee	3	3	3	3	3
NO.	6	7	8	9	10
Fixed investment	360	250	290	200	300
Capacity	58	70	56	48	40
Circulation transfer fee	3	3	3	3	3

Table 9. The requirement of customers

Customer	1	2	3	4	5
Requirement	6	7	9	8	8
Customer	6	7	8	9	10
Requirement	5	6	6	6	8
Customer	11	12	13	14	15
Requirement	7	6	4	3	2
Customer	16	17	18	19	20
Requirement	7	5	7	5	6

Table 10 shows the selection strategy of distribution centers and the specific distribution routes for customers based on AFSA optimization algorithm. Table 11 indicates the selection strategy of distribution centers and the specific distribution routes for customers based on the BCC-AFSA. Table 12 demonstrates the performance comparison of distribution center selection strategy between AFSA optimization algorithm and BCC-AFSA.

Table 10. Site selection plan of AFSA

selection strategy	Customers
9	5,6,7,12,14,16,17
1	2,4,10,13,18,19
7	1,3,8,9,11,15,20

Table 11. Site selection plan of BCC-AFSA

selection strategy	Customers
7	1,2,6,10,11,13,17
2	3,4,14,15,18,20
9	5,7,8,9,12,16,19

Table 12. Performance comparison

	AFSA	BCC-AFSA
The best cost	8020	7990
The worst cost	8210	8030
Average	8112	8003
Standard deviation	62.32	14.94
Average Convergence algebra	57.4	39.7
Average value of the difference	92	13

Figure 10 depicts the selection strategy of distribution centers based on AFSA optimization algorithm, while Figure 11 shows that of BCC-ACO optimization algorithm. In addition, Figure 12 demonstrates the optimization curve comparison of AFSA optimization algorithm and BCC-AFSA.

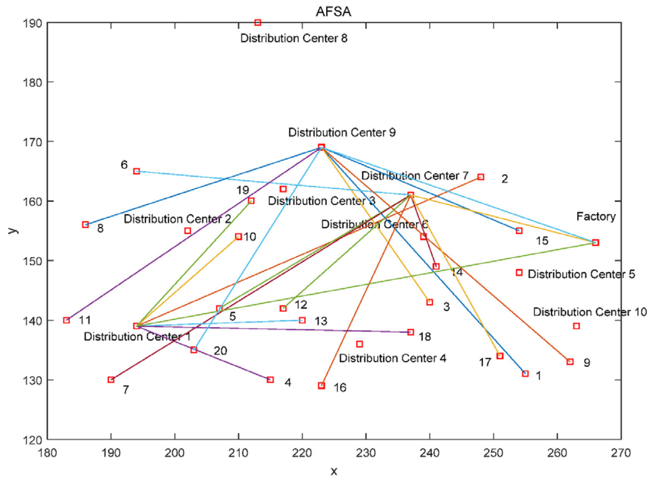

Figure 10. Distribution center selection strategy chart of AFSA

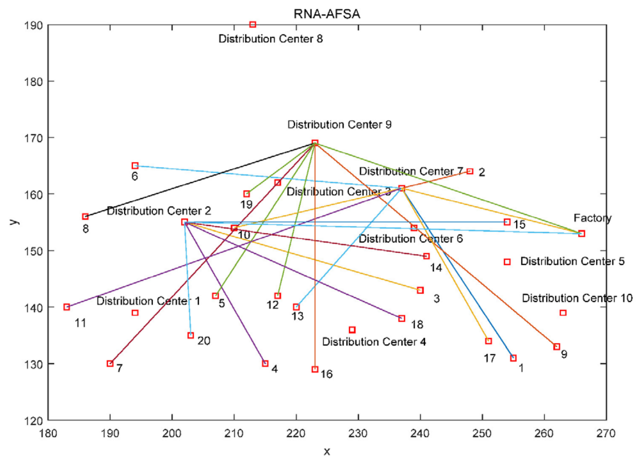

Figure 11. Distribution center selection strategy chart of BCC-AFSA

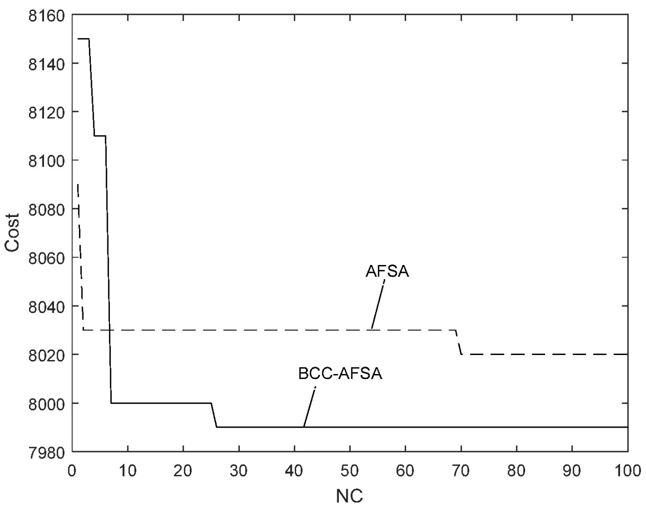

Figure 12. The comparison about the optimization curve

It can be deduced from the example simulations that:

(1) The total cost: In AFSA optimization algorithm the minimum total cost is 8020, while that of BCC-AFSA is 7990, which is reduced by 0.37%. The average total cost of AFSA optimization algorithm is 8112, while that of BCC-AFSA is 8003, which is reduced by 1.34%. It can be concluded that BCC-AFSA can obtain the location optimization strategy with lower total cost, thus serving and reducing costs for manufacturers better.

(2) Convergence of the algorithm: The average optimization generation of AFSA optimization algorithm is 57.4, while that of BCC-AFSA is 39.7. It can be deduced that the convergence ability of BCC-AFSA behaves better in the selection strategy of distribution centers.

(3) Stability: Standard deviation and mean value of difference are applied to evaluate the stability. The standard deviation of AFSA and BCC-AFSA are 62.32 and 14.94, respectively, while the mean values of difference of those are 92 and 13, respectively. As s conclusion, BCC-AFSA shows better stability in the selection strategy of distribution centers.

7 Conclusions

First of all, this paper introduces the significance of the study of location problem, and on this basis, it summarizes the literature of location problem in the second part. The third part introduces the basic fish swarm algorithm model, the fourth part establishes the location model of distribution center, the fifth part introduces the artificial fish swarm algorithm improved by bacterial colony chemotaxis algorithm, the sixth part uses the improved fish swarm algorithm to solve the model, and the seventh part tests and simulates the improved algorithm.

In the article, a location selection strategy of distribution centers in logistics systems based on BCC-AFSA is established. In order to solve the problems such as falling into local optima easily and poor convergence accuracy, BCC is applied to the original algorithm, which enhances the global search ability and improves the convergence speed as well as the convergence accuracy. The effectiveness of the original algorithm is verified by comparing the test functions. Finally, the BCC-AFSA is adopted to optimize the location selection model of logistics distribution centers. The simulations indicate that BCC-AFSA can reduce the total cost remarkably, at the same time, select the feasible distribution centers rapidly can be reduced as well. However, the proposed primary algorithm is in the preliminary research, and thus further research is still required. In addition, the location selection model of distribution centers is inaccessible to completely simulate the practical situation and therefore remains in the initialization phase. Therefore, the model construction for more practical situation is an essential research direction in our further research.

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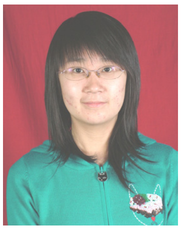
Biographies



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